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# PARALLELISM AND ROBUSTNESS IN GMRES WITH THE NEWTON BASIS AND THE DEFLATED RESTARTING

DESIRE NUENTSA WAKAM\* AND JOCELYNE ERHEL†

**Abstract.** The GMRES iterative method is widely used as Krylov subspace technique for solving sparse linear systems when the coefficient matrix is nonsymmetric and indefinite. The Newton basis implementation has been proposed on distributed memory computers as an alternative to the classical approach with the Arnoldi process. The aim of our work here is to introduce a modification based on deflation techniques. This approach builds an augmented subspace in an adaptive way to accelerate the convergence of the restarted formulation. In our numerical experiments, we show the benefits of using this implementation with hybrid direct/iterative methods to solve large linear systems.

**Key words.** Augmented Krylov subspaces, Adaptive Deflated GMRES, Newton basis, Hybrid linear solvers

**AMS subject classifications.** 65F10, 65F15, 65F22

**1. Introduction.** In this paper, we are interested in solving large systems of linear algebraic equations

$$Ax = b, \tag{1.1}$$

where  $A$  is a  $n \times n$  real nonsingular matrix,  $b$  and  $x$  are  $n$ -dimensional real vectors. Practical algorithms transform the original problem (1.1) to the following

$$M_L^{-1}AM_R^{-1}\tilde{x} = M_L^{-1}b, \quad \tilde{x} = M_Rx \tag{1.2}$$

where  $M_L^{-1}$  and  $M_R^{-1}$  are the action of preconditioning the system at left ( $M_R = I$ ), at right ( $M_L = I$ ) or both. On parallel computers, we assume that these preconditioners are formulated from some algebraic decomposition of the input matrix. However, they can be any approximation of the inverse of the matrix  $A$  and we refer the reader to the survey on the preconditioning techniques [9]. These preconditioners are generally combined with Krylov subspace methods as accelerators. The GMRES method [39] is widely used in this context. From this method, many improvements have been proposed to enhance its robustness and parallel efficiency; see for instance [6, 10, 12, 19, 22, 20, 30, 40, 23, 36]. In this work, we propose a new formulation of the method which combines two main approaches, namely the Newton basis GMRES [6] and the augmented basis for the restarted GMRES [30]. Our approach benefits from the enhanced parallelism in the former and the robustness in the latter. For the sake of clarity, we give here the formulation of the GMRES algorithm as first proposed by Saad and Schultz [39].

We consider in this paper the right preconditioned matrix  $B \equiv AM^{-1}$ . The proposed algorithms can be derived with less effort for the left preconditioned matrix. Given an initial guess  $x_0$ , the GMRES method finds the  $j$ -th approximate solution  $x_j$  of the form

$$x_j \in x_0 + M^{-1}\mathcal{K}_j(B, r_0), \tag{1.3}$$

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where  $r_0 = b - Ax_0$  is the initial residual vector and  $\mathcal{K}_j(B, r_0)$  is the  $j$ -th Krylov subspace defined as

$$K_j(B, r_0) = \text{span}\{r_0, Br_0, \dots, B^{j-1}r_0\}. \quad (1.4)$$

The goal behind GMRES is to minimize at each step the Euclidian norm of the residual, i.e

$$\|b - Ax_j\| = \min_{u \in x_0 + M^{-1}\mathcal{K}_j(B, r_0)} \|b - Au\|. \quad (1.5)$$

An orthonormal basis  $V_{j+1} = [v_0, \dots, v_j]^1$  of  $\mathcal{K}_{j+1}(B, r_0)$  is generated such that

$$v_0 = r_0/\beta, \quad \beta = \|r_0\|, \quad BV_j = V_{j+1}H_{j+1,j} = V_jH_j + h_{\{j+1,j\}}v_je_j^T, \quad (1.6)$$

It is therefore proved [38] that (1.5) reduces to

$$\|\beta e_1 - H_{j+1,j}y_j\| = \min_{y \in \mathbb{R}^j} \|\beta e_1 - H_{j+1,j}y\| \quad (1.7)$$

and the approximate solution  $x_j$  can be written as

$$x_j = x_0 + M^{-1}V_jy_j. \quad (1.8)$$

Our work combines two improvements of this method. In GMRES( $m$ ), the method restarts at some step  $m$  to save the storage and the computational requirements as the iterations proceed. The deflated and augmented approaches [5, 10, 22, 26, 30] keep some useful information at the time of the restart to enhance robustness. We briefly review these methods in section 2. The second improvement builds the orthonormal basis with a parallel algorithm that reduces the number of exchanged MPI messages on distributed-memory computers. Indeed, the time to exchange a MPI message of size  $n$  words is given by  $\gamma + \delta \cdot n$  where  $\gamma$  is the network latency (in seconds) and  $\delta$  is the inverse bandwidth (in seconds per word). Hence, reducing the number of MPI messages is equivalent to minimize the overhead due to this latency. From the original formulation of GMRES, the basis  $V$  is built and orthogonalized by the modified Gram-Schmidt implementation (MGS) of the Arnoldi process ( $V$  is referred to as *Arnoldi basis*). This process induces a high communication overhead due to the numerous inner products : for instance, a GMRES cycle of  $m$  iterations requires approximately  $\frac{1}{2}(m^2 + 3m)$  global communications for the inner products. On high latency networks, the start-up time due to these collective communication can easily dominate. Moreover, the kernel operations in MGS have a very low granularity which does not fully benefit from the computer architecture. In the classical Gram-Schmidt implementation (CGS) of the Arnoldi process, the communication time can be reduced by accumulating and broadcasting multiple inner products together. However the low granularity of the kernel operations in the orthogonalization procedure remains because of the sequential form of the Arnoldi process. Moreover, CGS is more sensitive to rounding errors than MGS [24]. Alternative implementations [6, 15, 19, 20, 23, 25, 40, 36] have been proposed. They divide the process into two main phases : first, a nonorthogonal basis of the Krylov subspace is generated and orthogonalized as a group of vectors in the second phase. As first proposed by Bai, Hu and Reichel [6], the *a priori* basis is built with the aid of Newton polynomials.

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<sup>1</sup>Throughout this paper, we use a zero-based numbering for all the vectors in the basis

We will refer to this as the *Newton-basis GMRES*. Later on, the orthogonalization is done by replacing the vector-vector operations of the MGS method by the task of computing a  $QR$  factorization of a dense method. De Sturler [15] analyzes the parallel implementation of the second phase and suggests a distributed MGS factorization to overlap communication with computation. Sidje and Philippe [41], Erhel [19] and Sidje [40] use a different orthogonalization strategy called RODDEC which combines the Householder factorization with Givens rotations and requires only point-to-point communication. Demmel et al [16] propose a different  $QR$  factorization called *Tall Skinny QR* (TSQR) which reorganizes the computation to reduce the memory access and exploit the data locality.

Our proposal in this work is to combine the Newton-basis GMRES with the augmented and deflated GMRES. The new approach is simple and can be used together with any of the previous orthogonalization strategies once the augmented *a priori* basis is built. The motivation of our work is two-fold: previous studies [36] have shown that when the size of the Newton basis grows, the vectors become increasingly dependent. As a result, the method may experience a slow convergence rate. With the new approach, the basis is kept small and augmented with some useful approximate eigenvectors. The second motivation is related to GMRES( $m$ ) preconditioned by domain decomposition methods. Indeed, with Schwarz-based preconditioners, when the number of subdomains increases, the preconditioner becomes less and less robust and the method requires more iterations to converge. In this situation, the basis size is usually increased to prevent the stagnation. In the proposed approach, we show that by adding adaptively more approximate eigenvectors, the convergence rate is improved. Recently, Mohiyuddin et al [29] and Hoemmen [23] propose a new formulation in their *communication avoiding* GMRES which does not require the Krylov basis size to be equal to the number of vectors generated *a priori*. Their formulation builds the Krylov basis with several steps of the Arnoldi process where each step builds a set of vectors with the Newton polynomials. Our proposed approach can be used as well with their formulation for the problems that are very sensitive to the restarting procedure in GMRES. We show indeed in section 3 how the augmented basis can be formulated in their proposed approach. The remaining part of this paper is organized as follows : in section 2, we review briefly how the deflation of eigenvalues is used in the restarted GMRES. In section 3, we derive the new approach combining deflation to the Newton basis GMRES and we discuss on the parallel implementation. section 4 is focused on numerical experiments to show the benefits of the proposed approach.

**2. Restarted GMRES accelerated by deflation.** A practical implementation of GMRES is based on restarting a minimum residual iteration when the correction space reaches a given dimension  $m$ . At the time of restart, information from the previous Krylov subspace is discarded and the orthogonality between successive Krylov subspaces is not preserved. The worst case is when the successive generated Krylov subspaces are very close. As a result, there is no significant reduction in the residual norm and the iterative process stagnates. Deflation techniques are a class of acceleration strategies that collect useful information at the time of restart mainly to avoid this stagnation and improve the convergence rate. The main idea behind these methods is to remove the smallest eigencomponents from the residual vector as they are known to slow down the convergence of GMRES [46]. For a general analysis of acceleration strategies in the minimal residual methods, we refer the reader to Eiermann, Ernst, and Schneider [17]. For the general Krylov subspace methods, the recent reviews in [21, 43] are also of great interest.

In deflation techniques, the Krylov subspaces are enriched by some approximation of invariant subspaces associated to a selected group of eigenvalues (generally the smallest ones). Two strategies are often used, namely by preconditioning the linear system [10, 19, 26] or by augmenting the Krylov subspace [30, 31].

Let  $\lambda_1, \lambda_2, \dots, \lambda_n$  be the eigenvalues of  $B$ . Consider an exact invariant subspace of dimension  $r$  corresponding to the  $r$  smallest eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_r$  and an orthonormal basis of this subspace, written  $U$  in the matrix form. Using the preconditioner  $\bar{M}^{-1}$  defined as:

$$\bar{M}^{-1} = I_n + U(|\lambda_n|T^{-1} - I_r)U^T, \quad T = U^T B U, \quad (2.1)$$

the eigenvalues of  $B\bar{M}^{-1}$  are  $\lambda_{r+1}, \dots, \lambda_n, |\lambda_n|$  with a multiplicity at least  $r$  [22]. Then, GMRES( $m$ ) applied to  $B\bar{M}^{-1}$  converges faster since the smallest eigencomponents that slow down the convergence are deflated. In practice,  $U$  is replaced by a basis of an approximate invariant subspace.

The actual implementation in [22] and the improvements in [10] rely on the approximation of  $U$  which is updated at each restart by computing the Ritz values from the Arnoldi relation in equation (1.6) to yield a more accurate basis. In [5],  $U$  is computed by the Implicit-Restarted Arnoldi (IRA) process and the result is used to form a left preconditioner. The adaptive preconditioner by Kharchenko and Yeremin [26] is built such that the Ritz values which approximate the largest eigenvalues of  $B$  are translated to a cluster around one.

Complexity overhead is similar in the preconditioning and the augmented subspace approaches. In both cases, computing a new basis at each restart involves a small eigenvalue problem. Also, it is easy to update the preconditioning matrix with a new basis  $U$  [10]. However, applying the preconditioner  $\bar{M}^{-1}$  in equation (2.1) may induce overhead with a large number of processors, because of global MPI reduction operations. On the other hand, in the augmented approach presented below [30, 31], the communication is reduced since there is no global reduction operation.

The augmented approaches form the new approximation with a projection onto a subspace  $\mathcal{C} = \mathcal{K}_m(B, r_0) + \mathcal{W}$ , where  $\mathcal{W} = \text{span}\{u_0, \dots, u_{r-1}\}$ . Minimal changes are required to the existing kernel operations as the vectors are directly added to the existing Krylov basis. Moreover, when the vectors  $u_0, \dots, u_{r-1}$  are the harmonic Ritz vectors, Morgan [31] shows that the augmented subspace  $\mathcal{C}$  is itself a Krylov subspace and writes

$$\mathcal{C} = \mathcal{K}_m(B, r_0) + \mathcal{W} = \mathcal{K}_{m+r}(B, q_m(B)r_0), \quad (2.2)$$

where  $q_m(B)$  is a polynomial of degree at most  $m$ .

**3. Deflated GMRES in the Newton basis.** In this section, We derive the new implementation of the GMRES algorithm where the Krylov subspace is spanned by the Newton polynomials and augmented with eigenvectors. Compared to the previous Newton basis implementations [6, 19, 40, 23], the main difference is that the new approach uses the deflation strategies to recover the information that is lost at the time of restart. Hence for the problems that are sensitive to the restarting procedure, our implementation should converge faster than the previous approaches for the same basis size. Compared to the GMRES-E by Morgan [30], our approach communicates less and should produce kernels that are better suited for parallel computations. Compared to GMRESDR of Morgan [31] however, we have not investigated whether the proposed augmented basis is itself a Krylov basis and we left it as future work.

**3.1. Augmenting the Newton basis.** We now derive the proposed approach. Our motivation is to get a Arnoldi-like relation for the augmented basis when the eigenvectors are added at the end of the Newton basis. Let  $B$  be the preconditioned matrix,  $x_0$  an initial guess and  $r_0$  the initial residual vector. A  $m$ -dimensional Krylov subspace is spanned by the Newton polynomials applied to  $r_0$  of the form

$$\mathcal{P}_{j+1}(B) := \sigma_{j+1}(B - \lambda_{j+1}I)\mathcal{P}_j(B), \quad j = 0, 1, 2, \dots, \quad (3.1)$$

where  $\mathcal{P}_0(B) := r_0$ ,  $\sigma_j$  and  $\lambda_j \in \mathbb{R}$  (See [6, 36]). We discuss later on the choice of these scalars.

Let  $\mathcal{W} = \text{span}\{u_0, u_1, \dots, u_{r-1}\}$  be a coarse subspace of dimension  $r$ . We discuss about the computation of these vectors in section 3.2.5. Let  $s = m + r$  and  $\mathcal{C}_s$  the augmented subspace defined by

$$\mathcal{C}_s = \mathcal{K}_m(B, r_0) + \mathcal{W} \quad (3.2)$$

as previously. We write the basis of  $\mathcal{W}$  in the matrix form as

$$U_r = [ u_0 \quad \dots \quad u_{r-1} ].$$

We also define the augmented subspace  $\mathcal{C}_{s+1}$  by

$$\hat{\mathcal{C}}_{s+1} = \mathcal{K}_{m+1}(B, r_0) + BW \quad (3.3)$$

**PROPOSITION 3.1.** *Suppose that  $\dim(\mathcal{C}_{s+1}) = s + 1$ , there exists an orthonormal basis  $\mathbf{V}_{s+1} = [ V_{m+1} \quad \hat{V}_r ] \in \mathbb{R}^{n \times (s+1)}$  of the subspace  $\hat{\mathcal{C}}_{s+1}$  such that  $V_{m+1}$  is an orthonormal basis of  $\mathcal{K}_{m+1}(B, r_0)$  and*

$$\mathbf{W}_s = [ V_m \quad U_r ] \quad (3.4)$$

is a basis of  $\mathcal{C}_s$ . These basis are related by an Arnoldi-like relation written

$$B\mathbf{W}_s = \mathbf{V}_{s+1}\bar{\mathbf{H}}_s = \mathbf{V}_s\mathbf{H}_s + \mathbf{h}_{s+1,s}v_{s+1}e_s^T, \quad (3.5)$$

where  $\bar{\mathbf{H}}_s \in \mathbb{R}^{(s+1) \times s}$  is an upper Hessenberg matrix. Moreover, the vector  $x_s \in \mathbb{R}^n$  given by

$$x_s = x_0 + M^{-1}\mathbf{W}_s y_s, \quad (3.6)$$

where  $y_s \in \mathbb{R}^n$  solves the least-square problem  $J_s(y)$  defined by

$$J_s(y) = \|\beta e_1 - \bar{\mathbf{H}}_s y\|_2, \quad \beta = \|r_0\|_2 \quad (3.7)$$

minimizes the residual norm  $\|b - Ax_s\|$  over  $x_0 + M^{-1}\mathcal{C}_s$ .

*Proof.* From  $k_0 = r_0/\|r_0\|_2$ , a set of vectors  $k_j$  can be generated such that

$$\sigma_{j+1}k_{j+1} = \begin{cases} (B - \lambda_{j+1}I)k_j & \text{if } 0 \leq j \leq m-1 \\ Bu_{j-m} & \text{if } m \leq j \leq s-1. \end{cases} \quad (3.8)$$

where  $\lambda_j$  and  $\sigma_j$ , ( $j = 1, 2, \dots$ ) are user-specified real scalars. We discuss in sections 3.2.1 and 3.2.2 on their optimal choice. In matrix form, the relation (3.8) writes

$$\begin{cases} BK_m = K_{m+1}\bar{T}_m \\ BU_r = \hat{K}_r D_r \end{cases} \quad (3.9)$$

with  $K_{m+1} = [k_0 \ k_1 \ \dots \ k_m]$ ,  $\hat{K}_r = [k_{m+1} \ \dots \ k_s]$ ,

$$\bar{T}_m = \begin{bmatrix} \lambda_1 & & & & & & & & & & \\ \sigma_1 & \lambda_2 & & & & & & & & & \\ & \sigma_2 & \lambda_3 & & & & & & & & \\ & & & \ddots & & \ddots & & & & & \\ & & & & & & \lambda_{m-1} & & & & \\ & & & & & & \sigma_{m-1} & & & & \lambda_m \\ & & & & & & & & & & \sigma_m \end{bmatrix} \in \mathbb{R}^{(m+1) \times m}, \quad (3.10)$$

and  $D_r = \text{diag}\{\sigma_{m+1}, \dots, \sigma_s\} \in \mathbb{R}^{r \times r}$ .

A  $QR$  factorization of  $[K_{m+1} \ \hat{K}_r]$  yields

$$[K_{m+1} \ K_r] = \mathbf{v}_{s+1} \mathbf{R}_{s+1} = [V_{m+1} \ \hat{V}_r] \begin{bmatrix} R_{m+1} & R_{m+1,r} \\ 0 & R_r \end{bmatrix}. \quad (3.11)$$

Thus we get  $BV_m = BK_m R_m^{-1} = V_{m+1} R_{m+1} \bar{T}_m R_m^{-1}$  and  $BU_r = \hat{K}_r D_r = (V_{m+1} R_{m+1,r} + \hat{V}_r R_r) D_r$ .

Using equations (3.9) and (3.11), we get

$$B\mathbf{w}_s = \mathbf{v}_{s+1} \bar{\mathbf{H}}_s, \quad (3.12)$$

where

$$\bar{\mathbf{H}}_s = \mathbf{R}_{s+1} \begin{bmatrix} \bar{T}_m & 0 \\ 0 & D_r \end{bmatrix} \begin{bmatrix} R_m^{-1} & 0 \\ 0 & I_r \end{bmatrix} = \begin{bmatrix} H_s \\ h_{s+1,s} e_s^T \end{bmatrix}. \quad (3.13)$$

The first part is thus proved (equation 3.5).

The second part of the proposition is similar to the optimality property in the augmented GMRES [12, Algorithm 2.1]. Consider an arbitrary vector  $x_s = x_0 + M^{-1}\mathbf{w}_s y$  in the affine space  $x_0 + M^{-1}\mathcal{C}_s$ , the corresponding residual vector can be expressed as:

$$b - Ax_s = b - A(x_0 + M^{-1}\mathbf{w}_s y) \quad (3.14)$$

$$= r_0 - \mathbf{v}_{s+1} \bar{\mathbf{H}}_s y$$

$$= \beta k_0 - \mathbf{v}_{s+1} \bar{\mathbf{H}}_s y$$

$$= \mathbf{v}_{s+1} (\beta e_1 - \bar{\mathbf{H}}_s y) \quad (3.15)$$

where  $\beta = \|r_0\|$  and  $e_1 = [1, 0, \dots, 0]^T$ . If we denote by  $J_s(y)$  the function

$$J_s(y) = \|b - A[x_0 + M^{-1}\mathbf{w}_s y]\|_2,$$

it comes from equation 3.15 and the fact that  $\mathbf{v}_{s+1}$  is orthogonal that

$$J_s(y) = \|\beta e_1 - \bar{\mathbf{H}}_s y\|_2. \quad (3.16)$$

Thus by taking the vector  $y_s \in \mathbb{R}^m$  which minimizes the function  $J_s(y)$ , the approximate solution  $x_s = x_0 + M^{-1}\mathbf{w}_s y_s$  will have the smallest residual in  $x_0 + M^{-1}\mathcal{C}_s$ .  $\square$

We refer to the matrix  $\mathbf{w}_s$  as the *augmented Newton basis* of the subspace  $\mathcal{C}_s$ , and to the matrix  $\mathbf{v}_{s+1}$  as the *augmented orthonormal basis* of the subspace  $\hat{\mathcal{C}}_{s+1}$ .

The induced GMRES is the *augmented Newton basis GMRES*, which we denote by AGMRES.

It is also possible to choose  $[K_m \ U_r]$  as a basis of  $\mathcal{C}_s$ , avoiding the computation of  $R_m^{-1}$ . However, the vectors  $U_r$  are computed at each restart by using a Rayleigh-Ritz procedure (see section 3.2.5), which requires the storage of  $V_{s+1}$  and the computation of  $V_{s+1}^T W_s$ . Thus, it saves memory and computation to choose  $W_s = [V_m \ U_r]$ .

This proof assumes that the basis vectors  $k_j, j = 0, \dots, s$  are generated through one pass in the kernel computation of equation 3.8. There are some situations where  $m$  is too large to guarantee a good robustness (ill-conditioned basis) or good performance (best value for data locality in multicore nodes). In a recent work, Hoemmen [23] uses the  $\mu$ -step Arnoldi of Kim and Chronopoulos [27]<sup>2</sup> in his *Arnoldi*( $\mu, t$ ) to build the basis vectors through multiple passes of the kernel computation in equation 3.8. Hence the process of computing  $s$  basis vectors is divided into  $t$  steps where each step generates  $\mu$  basis vectors with the Newton polynomials. The restart length is thus  $s = \mu \cdot t$ . We show in the following that the proposition 3.1 holds in the case of a  $\mu$ -step basis. We explain the basis idea with  $t = 2$ .

Let  $k_0$  be the starting vector and  $s = \mu \cdot t + r = m + r$ . As from the first part of equation 3.8 we generate the sequence of vectors

$$\sigma_{j+1}k_{j+1} = (B - \lambda_{j+1}I)k_j, 0 \leq j \leq \mu - 1. \quad (3.17)$$

It comes that

$$BK_\mu^{(0)} = K_{\mu+1}^{(0)}\bar{T}_\mu^{(0)} \quad (3.18)$$

where  $K_{\mu+1}^{(0)} = [k_0, k_1, \dots, k_\mu] \in \mathbb{R}^{n \times (\mu+1)}$ ,  $\bar{T}_\mu^{(0)} \in \mathbb{R}^{(\mu+1) \times \mu}$  is a bidiagonal matrix. A  $QR$  factorization of  $K_{\mu+1}^{(0)}$  gives

$$K_{\mu+1}^{(0)} = V_{\mu+1}^{(0)}R_{\mu+1}^{(0)} \quad (3.19)$$

and thus

$$BK_\mu^{(0)} = V_{\mu+1}^{(0)}\bar{H}_\mu^{(0)} = V_\mu^{(0)}H_\mu^{(0)} + h_{\mu+1,\mu}V_{\mu+1}^{(0)}e_\mu e_\mu^T, \quad (3.20)$$

where  $\bar{H}_\mu^{(0)} = R_{\mu+1}^{(0)}\bar{T}_\mu^{(0)}$  and  $e_\mu$  is the  $\mu^{th}$  unit vector. This first step is just the derivation of the Arnoldi-like relation for the (non-augmented) Newton basis. Note that we don't have a mathematically equivalent Arnoldi relation as in equation 1.6.  $\bar{H}_{\mu+1}^{(0)}$  is not equal in exact arithmetic to the Hessenberg matrix  $\bar{H}$  of that equation as we avoid dealing with the term  $(R_{\mu+1}^{(0)})^{-1}$ . However, the columns of  $V_{\mu+1}^{(0)}$  form an orthogonal basis of a  $\mu$ -dimensional Krylov basis. From its last column as a starting vector, we can thus build the second  $\mu$ -step basis. At this step, we add the eigenvectors in the subspace by augmenting the  $\mu$ -step basis.

Let  $k_\mu = V_{\mu+1}^{(0)}e_\mu$ , a  $\mu$ -step augmented basis is generated as follows:

$$\sigma_{j+1}k_{j+1} = \begin{cases} (B - \lambda_{\mu-j+1}I)k_j & \text{if } \mu \leq j \leq m - 1 \\ Bu_{j-m} & \text{if } m \leq j \leq s - 1. \end{cases} \quad (3.21)$$

<sup>2</sup>The original method is referred to as  $s$ -step Arnoldi instead of  $\mu$ -step Arnoldi but we choose  $\mu$  here to differentiate with the size  $s$  of our augmented basis.



In matrix form, we get

$$B \begin{bmatrix} K_\mu^{(1)} & U_r \end{bmatrix} = K_{\mu+r+1}^{(1)} \begin{bmatrix} \bar{T}_\mu^{(1)} & 0 \\ 0 & D_r \end{bmatrix} \quad (3.22)$$

The matrices  $\bar{T}_\mu^{(1)}$  and  $D_r$  are analogous to the matrices in equation 3.5. At this point, to avoid loss of orthogonality, the vectors  $K_{\mu+r+1}^{(1)} = [k_\mu, k_{\mu+1}, \dots, k_{\mu+m+r}]$  should be orthogonalized against the previous vectors  $V_\mu^{(0)}$ . This can be done with a block Gram-Schmidt method which is equivalent to write<sup>3</sup>

$$\hat{K}_{\mu+r+1}^{(1)} = \left( I - V_\mu^{(0)}(V_\mu^{(0)})^T \right) K_{\mu+r+1}^{(1)}. \quad (3.23)$$

Note that the same stability problems may arise just as in the classical Gram-Schmidt process. We discuss on this issue at the end of this subsection. So far, the vectors  $\hat{K}_{\mu+r}^{(1)}$  are orthogonal to the basis vectors but it remains to orthogonalize them between each other. This can be done with a dense  $QR$  factorization to produce

$$\hat{K}_{\mu+r+1}^{(1)} = V_{\mu+r+1}^{(1)} R_{\mu+r+1}^{(1)}. \quad (3.24)$$

From equations 3.20 and 3.22, we get

$$B \begin{bmatrix} K_\mu^{(0)} & K_\mu^{(1)} & U_r \end{bmatrix} = \begin{bmatrix} V_\mu^{(0)} & K_{\mu+r+1}^{(1)} \end{bmatrix} \begin{bmatrix} H_\mu^{(0)} & 0 \\ h_{\mu+1,\mu} e_1 e_\mu^T & \bar{C}_{\mu+r} \end{bmatrix} \quad (3.25)$$

where

$$\bar{C}_{\mu+r} = \begin{bmatrix} \bar{T}_\mu^{(1)} & 0 \\ 0 & D_r \end{bmatrix}$$

Knowing that a  $QR$  factorization update have been performed on  $K_{\mu+r+1}^{(1)}$ , we get from equations 3.23 and 3.24 that,

$$\begin{bmatrix} V_\mu^{(0)} & K_{\mu+r+1}^{(1)} \end{bmatrix} = \begin{bmatrix} V_\mu^{(0)} & V_{\mu+r+1}^{(1)} \end{bmatrix} \begin{bmatrix} I & (V_\mu^{(0)})^T K_{\mu+r+1}^{(1)} \\ 0 & R_{\mu+r+1}^{(1)} \end{bmatrix}. \quad (3.26)$$

Substituting 3.26 in 3.25, we get

$$B W_s = V_{s+1} \bar{H}_s \quad (3.27)$$

where  $W_s = \begin{bmatrix} K_\mu^{(0)} & K_\mu^{(1)} & U_r \end{bmatrix}$ ,  $V_{s+1} = \begin{bmatrix} V_\mu^{(0)} & V_{\mu+r}^{(1)} \end{bmatrix}$  and

$$\bar{H}_s = \begin{bmatrix} I_{\mu,\mu} & (V_\mu^{(0)})^T K_{\mu+r+1}^{(1)} \\ 0 & R_{\mu+r+1}^{(1)} \end{bmatrix} \begin{bmatrix} H_\mu^{(0)} & 0 \\ h_{\mu+1,\mu} e_1 e_\mu^T & \bar{C}_{\mu+r} \end{bmatrix}.$$

From the fact that  $K_{\mu+r+1}^{(1)} e_1$  is orthogonal to  $V_\mu^{(0)}$  and that  $R_{\mu+r+1}^{(1)} e_1 = e_1$ , we get

$$\bar{H}_s = \begin{bmatrix} H_\mu^{(0)} & (V_\mu^{(0)})^T K_{\mu+r+1}^{(1)} \bar{C}_{\mu+r} \\ h_{\mu+1,\mu} e_1 e_\mu^T & R_{\mu+r+1}^{(1)} \bar{C}_{\mu+r} \end{bmatrix} \quad (3.28)$$

---

<sup>3</sup>Note that the first vector  $k_\mu$  is already orthogonal to  $V_\mu^{(0)}$  but we choose to orthogonalize it again.

which is a Hessenberg matrix. The first part of the proposition 3.1 is thus proved and the second part is similar to the previous proof.

GMRES with the  $\mu$ -step Newton basis is useful to control the conditioning of the basis generated with the Newton polynomials by choosing a suitable value of  $\mu$ . On multicore nodes, a well chosen value of  $\mu$  will also improve the data locality during the computation of the kernel computations (Generation of the basis and orthogonalization) [16, 23]. The drawback with this formulation is that when the new set of basis vectors is orthogonalized against all the previous vectors already computed, it is important to perform a good  $QR$  factorization update. Sometimes when a block Gram-Schmidt process is used, a reorthogonalization strategy should be performed to avoid loss of orthogonality, see for instance [24]. This process induces more computational cost as the number  $t$  of steps increases. As for the scalar formulation, the augmented basis will thus help to reduce this cost by reducing the number of steps  $t$ . We do not further investigate reorthogonalization and we focus in this paper to the basic implementation of a  $(\mu + r)$ -step augmented Newton basis.

**3.2. AGMRES : Augmented Newton-basis GMRES.** This section discusses the parallel implementation of the GMRES method where the Newton basis is augmented with a few selection of approximate eigenvectors. The main steps are outlined in Algorithm 3.2.

If we compare AGMRES with the previous related implementations of the GMRES method, we can make the following observations :

- Compared to the standard GMRES method, AGMRES produces kernel that are better suited for parallel computations during the generation of the orthogonal Krylov basis in steps 6 and 8. However, in addition to the basis  $V_{m+1}$ , it keeps  $2r$  vectors  $U_r$  and  $\hat{V}_r$ . It is thus worth mentioning that  $\text{AGMRES}(m, r)$  requires as much memory as  $\text{GMRES}(m + 2r)$ . Nevertheless, we show in the provided numerical experiments that, on most test cases,  $\text{AGMRES}(m, r)$  produces a better convergence acceleration than  $\text{GMRES}(m + 2r)$  and even  $\text{GMRES}(2m)$ .
- The GMRES-E of Morgan [30] keeps a second basis as well. However its implementation is based on the Arnoldi process. It will thus communicate more for the same convergence behavior. Our implementation includes an adaptive strategy that will allow to increase the number of extracted eigenvectors if necessary.
- Compared to CA-GMRES of Hoemmen [23], our implementation is limited to one  $\mu$ -step Newton basis. However, we show in the previous section how an augmented basis can be defined for more than one  $\mu$ -step basis. For the same restart length,  $\text{CA-GMRES}(\mu, t)$  and  $\text{GMRES}(\mu \cdot t)$  produce the same convergence behavior.  $\text{AGMRES}(\mu \cdot t, r)$  is more likely to produce a faster convergence than these two approaches when the convergence rate is affected by the restarting procedure.

So far, the algorithm starts with an initial approximation of the solution vector  $x_0$  (in practice, we use a zero vector), the size  $m$  of the Krylov basis, the maximum number of iterations  $itmax$  allowed and the desired accuracy  $\epsilon$ . The remaining input values are used for the augmented basis: the number of eigenvectors  $r$  that are added at each step; the parameters  $l, rmax, smv$  and  $bgv$  for the adaptive strategy, see section 3.2.6. The main steps of the algorithm are the computation of the shifts (steps 1 and 3), the generation of the augmented Newton basis at step 6 and its orthogonalization in section 8. The approximate solution is updated at step 12. At step 21, we update the

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**Algorithm 1** AGMRES( $m, r$ ) : Augmented Newton-basis GMRES
 

---

**Require:**  $x_0, m, itmax, \epsilon, r, l, rmax, smv, bgv$ ;

- 1: **Perform** one cycle of GMRES( $m$ ) [39, Algorithm 4] to find a new approximation  $x_m$ , the residual  $r_m$  and the matrices  $H_m$  and  $V_m$  satisfying equation 1.6.  
**if** ( $\|r_m\| < \epsilon$ ) **return**
  - 2: Set  $x_0 \leftarrow x_m$  and  $r_0 \leftarrow r_m$ ;  $\beta = \|r_0\|$ ;
  - 3: **Compute**  $m$  Ritz values  $\{\lambda_j\}_{j=1}^m$  of  $AM^{-1}$  from  $H_m$  and order them with the Leja ordering [6].
  - 4: **If** ( $r > 0$ ) extract  $r$  Ritz vectors  $U_r$  for the augmented basis.
  - 5: **while** ( $\|r_0\| > \epsilon$ ) **do**
  - 6:   **Compute** the basis vectors of equation 3.8 [40, 19] to get  $K_{m+1}$  and  $\bar{T}_m$ .
  - 7:   **Compute**  $\hat{K}_r$  and  $D_r$  using the second part of equation 3.8.
  - 8:   **Compute** the  $QR$  factorization  $\begin{bmatrix} K_{m+1} & \hat{K}_r \end{bmatrix} = V_{s+1}R_{s+1}$ .
  - 9:   **Derive**  $W_s = \begin{bmatrix} V_m & U_r \end{bmatrix}$ .
  - 10:   **Compute** the  $(s+1) \times s$  Hessenberg matrix  $\bar{H}_s$  from equation 3.13
  - 11:   **Solve**  $y_s = \min \|\beta e_1 - \bar{H}_s y\|_2$
  - 12:   **Compute**  $x_s = x_0 + M^{-1}W_s y_s$ ,  $r_s = b - Ax_s$ ,  $it \leftarrow it + s$
  - 13:   **if** ( $\|r_s\| < \epsilon$  **or**  $it > itmax$ ) **return**
  - 14:   Set  $x_0 \leftarrow x_s$  and  $r_0 \leftarrow r_s$ ;
  - 15:   **if**  $r > 0$  **then**
  - 16:      $Iter = s * \log\left(\frac{\epsilon}{\|r_s\|}\right) / \log\left(\frac{\|r_s\|}{\|r_0\|}\right)$
  - 17:     **if** ( $Iter > smv * (itmax - it)$ ) **then**
  - 18:       **if** ( $(Iter > bgv * (itmax - it))$  **and** ( $r < rmax$ ) **and** ( $l > 0$ )) **then**
  - 19:          $r \leftarrow r + l$  /\*Increase the number of eigenvalues to deflate\*/
  - 20:       **end if**
  - 21:       **Replace** the  $r$  approximate eigenvectors  $u_0, u_1, \dots, u_{r-1}$  by  $r$  harmonic Ritz vectors of  $B \equiv AM^{-1}$
  - 22:     **end if**
  - 23:   **end if**
  - 24: **end while**
- 

eigenvectors to be added in the Newton basis. The adaptive strategy is implemented in steps 15-23 All these steps are explained in the next sections.

**3.2.1. Computation of the shifts.** The generation of the Krylov subspace with the Newton polynomials uses the scalars  $\lambda_j$ ,  $j = 1, \dots, m$  to produce a stable basis. Bai et al [6] show that a good choice would be to use the eigenvalues of  $B$  numbered according to the following modified *Leja order* (see [37]):

$$\begin{cases} |\lambda_1| = \max_{j=1, \dots, m} |\lambda_j| \\ \prod_{k=1}^j |\lambda_{j+1} - \lambda_k| = \max_{l=1, \dots, m} \prod_{k=1}^j |\lambda_l - \lambda_k|, \quad j = 1, \dots, m-1 \end{cases} \quad (3.29)$$

In practice, the spectrum of  $B$  is not available and very expensive to compute. In this situation, the Ritz values of  $B$  which are the eigenvalues of the Hessenberg matrix  $H_m$  in equation 1.6 are used. This implies that  $m$  steps of the Arnoldi process should be performed to get these values. At step 1, we perform one cycle of the Arnoldi-GMRES method. From this step, we get an approximation of the solution  $x_m$  and the associated residual  $r_m$ . This vector is used as the initial search direction for Newton-basis GMRES from step 5. At step 3, each process computes the eigenvalues of its own

copy of the Hessenberg matrix  $H_m$  and order them with the Leja ordering. This step uses so far the parallelism inside the matrix-vector product and the preconditioning operation. But it requires global communication as pointed out in section 1. Note that when  $m$  gets large, it may be expensive to perform this step of Arnoldi-GMRES. The cost here is compared to one step of the Newton basis GMRES mainly in terms of granularity and the volume of MPI messages. In practice, we use a small value of  $m$  to show the benefits of augmenting the basis. Nevertheless, if a large basis should be used, a solution could be to use a  $\mu$ -step basis as explained in the previous section. Another solution, as advised by Philippe and Reichel [36] is to perform one cycle of Arnoldi-GMRES with a smaller basis to get a subset of these values. From this subset, a convex hull is defined and continuously updated with new values collected during the Newton-basis GMRES iterations.

**3.2.2. Computation of the Newton basis with scaling factors.** The first  $m + 1$  vectors of  $K_{s+1}$  can be generated using Algorithm 1.1 in [40]; then it is easy to generate the last  $r$  vectors from  $U_r$ . Note that when a particular  $\lambda_{j+1}$  is complex, and assuming that  $Im(\lambda_{j+1}) > 0$  (This is always possible from the complex conjugate pairs and the modified Leja ordering), the complex arithmetic is avoided by writing the first part of equation 3.8 as

$$\begin{aligned}\sigma_{j+1}k_{j+1} &= (B - Re(\lambda_{j+1})I)k_j \\ \sigma_{j+2}k_{j+2} &= (B - \lambda_{j+1}I)(B - \bar{\lambda}_{j+1}I)k_j = \sigma_{j+1}(B - Re(\lambda_{j+1})I)k_{j+1} + Im(\lambda_{j+1})^2k_j.\end{aligned}$$

In this case, the matrix  $\bar{T} \in \mathbb{R}^{s+1 \times s}$  of equations 3.5 and 3.22 is tridiagonal. So far, the scalars  $\sigma_j, j = 1, \dots, m$  in equation 3.5 are used to control the growth of the vectors  $\{k_j\}_{j=1}^m$ . The common choice is to take  $\sigma_j = \|k_j\|$ . The parallelism inside this step is through the preconditioning and the parallel matrix-vector operations  $(AM^{-1} - \lambda I)k \equiv A(M^{-1}k) - \lambda k$ . When  $\sigma_j = \|k_j\|$ , then there are  $(m + r)$  global communications, which are far less than the  $\frac{1}{2}(m^2 + 3m)$  global communications in the Arnoldi process. With some particular cases, this norm can be computed distributively. When using for instance the explicit formulation of multiplicative Schwarz, the basis vectors are computed in a pipeline across all the subdomains. Each process is thus able to compute its own contribution to the norm and the basis vectors are normalized *a posteriori* [4, 32]. When the size of the basis is small enough, the rows and columns of the matrix can be equilibrated and no scaling, thus no global communication, should be needed during the computation of the basis vectors [23].

**3.2.3. Orthogonalization of the basis.** After the basis vectors are computed, they should be orthogonalized between each other at step 8 of Algorithm 3.2 to produce the orthogonal system  $V_{s+1}$ . At the end of the step 6, the vectors  $K_{s+1}$  are distributed on all processors as a contiguous blocks of rows which is equivalent to the classical 1D rowwise partitioning for the matrix-vector products. Any algorithm for the parallel dense QR factorization can now be used to orthogonalize the system  $K_{s+1}$ . In our implementation, we use the RODDEC algorithm described in [40, section 4.2]. This method performs first a Householder orthogonalization on each block of rows. This is done in a perfect parallel phase by all the processes having the rows. After that, the Givens rotations are used to annihilate the blocks below the first one. During this second step, the processors are placed on a ring topology and each process sends the required data on this ring. This step requires  $\mathcal{O}(m^2)$  point-to-point messages on a ring topology and the average message length is  $(m + 1)/2$  double precision number. The approach advocated in [13] maps the processors on a binary tree to

eliminate the extra triangular factors of RODDEC. The TSQR algorithm of Demmel *et al* [16] which gives a more general divide-and-conquer algorithm can be used as well at this step. It requires  $\mathcal{O}(\log(P))$  MPI messages where  $P$  is the total number of MPI processes sharing the system  $K_{s+1}$ .

**3.2.4. Updating the current approximation.** At the end of the  $QR$  factorization, the triangular matrix  $\mathbf{R}_s$  of equation 3.11 is usually available on one process. In the RODDEC algorithm, it is available in the last process. It can be broadcasted to all other processes such that the steps 10 and 11 are done by all the processes. When the number of MPI processes gets large, it is more efficient to perform these steps on the last process and to broadcast only the result of the least-squares problem at step 11. In our implementation, we choose to send a copy of the matrix since it is required by all processes to update the eigenvectors, see section 3.2.5. So far, the Hessenberg matrix  $\bar{\mathbf{H}}_s$  is assembled from  $\mathbf{R}_s$  and  $\bar{\mathbf{T}}_s$  using a modification of Algorithm 1.2 in [40]. The modification allows to take into account the scaling factors of the augmented vectors in the basis. A  $QR$  factorization is performed on the output Hessenberg matrix to solve the least-squares problem in the minimization step. The LAPACK routine *dgeqrf* is used for this purpose. The output solution is used to compute the new approximate solution at step 12. Note that since we are using right preconditioning, we can obtain an estimate of the true residual norm without explicitly computing the residual vector  $r_s$ . Nevertheless, at the time of restart, we need  $r_s$  for the new search direction.

**3.2.5. Updating the eigenvectors.** When the iterative process starts at line 16 of Algorithm 3.2, the eigenpairs  $(u_j, \lambda_j)$  of  $B \equiv AM^{-1}$  are approximated from the first GMRES( $m$ ) cycle with a standard projection technique as follows :

$$V_m^T(B - \lambda_j I)V_m g_j = 0 \quad (3.30)$$

leading to the eigenvalue problem

$$H_m g_j = \lambda_j g_j. \quad (3.31)$$

The Ritz values  $\lambda_j, j = 0, \dots, m-1$  are used as shifts for the Newton basis and the vectors  $u_j = V_m g_j, j = 0, \dots, m-1$  corresponding to the  $r$  smallest eigenvalues are used to augment the Newton basis.

Then to change the vectors  $U_r$  at step 21, we use a Rayleigh-Ritz procedure. Indeed, as advised by the previous studies [12, 30], this procedure does better at finding eigenvalues nearest zero. Using the augmented subspace  $\mathcal{C}_s$ , each extracted approximate eigenvector  $u$  is expressed as  $u = W_s g_i$ . Using  $BW_s$  and  $W_s$ , the Galerkin condition writes :

$$(BW_s)^T(B - \lambda_j I)W_s g_j = 0. \quad (3.32)$$

It comes with the relation 3.5 that,

$$\underbrace{\bar{\mathbf{H}}_s^T \bar{\mathbf{H}}_s}_{\mathbf{G}_s} g_j = \lambda_j \underbrace{\bar{\mathbf{H}}_s^T \mathbf{V}_{s+1}^T W_s}_{\mathbf{F}_s} g_j. \quad (3.33)$$

We thus obtain a dense generalized eigenvalue problem of size  $s \times s$  where  $(\lambda_j, W_s g_j)$  gives a harmonic Ritz pair of  $B$ . Multiplying  $\mathbf{F}_s$  and  $\mathbf{G}_s$  by  $\mathbf{H}_s^{-T}$ , we get

$$\begin{aligned} H_s^{-T} \mathbf{G}_s &= \mathbf{H}_s^{-T} \begin{bmatrix} \mathbf{H}_s^T & \alpha e_s \end{bmatrix} \begin{bmatrix} \mathbf{H}_s \\ \alpha e_m^T \end{bmatrix} \\ &= \mathbf{H}_s + \mathbf{h}_{s+1,s}^2 \mathbf{H}_s^{-T} e_s e_s^T \end{aligned} \quad (3.34)$$

$$H_s^{-T} \mathbf{F}_s = \begin{bmatrix} I_s & \mathbf{h}_{s+1,s} H_s^{-T} e_s \end{bmatrix} \mathbf{V}_{s+1}^T \mathbf{W}_s, \quad (3.35)$$

with  $\mathbf{V}_{s+1}^T \mathbf{W}_s = \begin{bmatrix} \mathbf{V}_{s+1}^T \mathbf{V}_m & \mathbf{V}_{s+1}^T U_r \end{bmatrix}$  and  $\mathbf{V}_{s+1}^T \mathbf{V}_m = \begin{bmatrix} I_m \\ 0 \end{bmatrix}$ .

The overhead here is small since it induces only  $r$  dot products of size  $n$  and a small generalized eigenvalue problem.

If the basis of  $\mathcal{C}_s$  is equal to  $\begin{bmatrix} K_m & U_r \end{bmatrix}$ , then the overhead is larger since it involves  $s$  dot products. Nevertheless, the numerical experiments show in most test cases that when the convergence is accelerated by deflation, the time to update the approximate eigenvectors is negligible compared to the total time saved without the deflation. Moreover, the adaptive strategy proposed next sets off deflation only if convergence is too slow.

**3.2.6. Adaptive strategy.** When the desired accuracy is not achieved, the method restarts and  $r$  new approximate eigenvectors (corresponding to the eigenvalues to deflate) are extracted from the  $s$ -dimensional subspace  $\mathcal{C}_s$ . This process may become expensive and is not beneficial if the convergence rate is not improved enough. We thus propose an adaptive strategy which detects if the deflation process will be beneficial to speedup the convergence or to avoid stagnation. This approach is based upon the work by Sosonkina *et al.* [45] which has been used successfully in another formulation of deflated GMRES[34]. At lines 16, based on the convergence rate already achieved, we estimate the remaining number of steps ( $Iter$ ) needed to reach the desired accuracy  $\epsilon$ . We use a small multiple ( $smv$ ) of the remaining number of steps to detect some insufficient reduction in the residual norm. If it is greater than a small multiple ( $smv$ ) of the number of steps allowed ( $itmax$ ), then we switch to the deflation. We use a large multiple ( $bgv$ ) of  $itmax$  to detect a near-stagnation in the iterative process. In this case, the number of eigenvectors to augment is increased by a fixed (small) value. Clearly with the parameters  $r, l, Iter, smv, bgv$ , the adaptive strategy can be sketched as follows :

- If  $Iter \leq smv * itmax$ , the convergence rate is good enough and no more update should be done on the eigenvectors already computed.
- If  $smv * itmax < Iter \leq bgv * itmax$ , there is an insufficient reduction in the residual norm and the  $r$  eigenvectors are updated for the next cycles of AGMRES.
- If  $Iter > bgv * itmax$ , a stagnation may have occurred and we increase the number of eigenvalues to extract/update by a fixed number  $l$ . This can be changed at runtime by the user. Otherwise stated,  $l = 1$  in all our test cases.

Note that there are more sophisticated methods to ensure that for some given values of  $m$ , GMRES( $m$ ) (and thus AGMRES( $m$ )) will not stagnate; see for instance [42, 44]. Our current stagnation test is computed *a posteriori* and should be mostly used to detect a very slow reduction in the residual norm. Although the proposed parameters are problem-dependent, they can be useful to avoid the stagnation if there are some previous knowledge in the convergence behavior for the problems under study. Some numerical results are given in this sense in the next section.

**4. Numerical experiments.** This section presents some numerical results to show the parallel efficiency and the numerical robustness of the proposed approach. We first present the template for all the numerical tests in section 4.1 and the test cases in section 4.2.

**4.1. Test routines and implementation notes.** Implementations are done using the PETSc routines and data structures [7, 8]. The algorithm 3.2 has been implemented by a *KSP* module called AGMRES using a locally modified version of PETSc revision 3.1.p8. It uses the routines for matrix-vector product, the application of the preconditioner and the other parallel linear algebra functions. It can be used transparently with any preconditioner implemented in the package including the domain decomposition preconditioners. We use so far the Restricted Additive Schwarz (RAS) method [11] applied as a right preconditioner in all our tests. The main steps are outlined in Algorithm 2. Note from the step 7 of our test routine that we compare

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**Algorithm 2** Test routine for the parallel computation of the system 1.2 using restricted additive Schwarz method and GMRES-based accelerator.

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- 1: Read the matrix from a binary file and store it in a distributed CSR format. Read the right-hand side vector and store it accordingly.
  - 2: Perform a parallel iterative row and column scaling on the matrix and the right-hand side vector [3].
  - 3: Partition the weighted graph of the matrix in parallel with PARMETIS.
  - 4: Redistribute the matrix and right-hand-side according to the PARMETIS partitioning.
  - 5: Define the overlap between the submatrices for the additive Schwarz preconditioner.
  - 6: Setup the submatrices (ILU or LU factorization using MUMPS [2]).
  - 7: Solve iteratively the system using either the KSP AGMRES (Algorithm 3.2) or the PETSc built-in KSP GMRES [39, Algorithm 4].
  - 8: Write the solution vector to a binary file.
- 

AGMRES with the classical implementation of GMRES. As stated earlier, either the classical Gram-Schmidt or the modified Gram-Schmidt can be used for the Arnoldi process. The main advantage of CGS over MGS is the number of MPI messages, the amount of MPI reductions and the granularity in the computational kernel. However, a practical implementation of CGS includes a possible refinement strategy to be as stable as MGS. During our numerical experiments however, this refinement was not used in CGS and we did not notice any difference between GMRES-MGS and GMRES-CGS. We therefore give the results of GMRES with CGS. Unless stated, the stopping criterion of GMRES and AGMRES is  $\frac{\|b - Ax\|}{\|b\|} < 10^{-10}$  and the maximum number of iterations is 1,000. In AGMRES, the residual norm is computed only at each outer iteration. In GMRES, it is available during each inner iteration. Note that since we are using a right preconditioner, this residual norm is obtained cheaply from the Givens rotations that are used to transform the Hessenberg matrix in equation 1.7 into a triangular matrix.

In the following, since right preconditioning is used, the number of iterations is understood as the total number of matrix-vectors products and preconditioning steps. Hence in GMRES( $m$ ), it is equivalent to the counts of  $A(M^{-1}k)$ . In AGMRES, it is equal to the size of the augmented basis times the restart cycles. So far, AGMRES( $m$ ) refers to the algorithm 3.2 without the deflation (i.e  $r = 0, l = 0$ ); In AGMRES( $m, r$ ),  $r$  vectors corresponding to the smallest harmonic Ritz values are added to the basis and replaced at each restart; With the adaptive strategy, when it is necessary,  $r$  is increased by  $l = 1$  (otherwise stated).

In these numerical experiments, the basis of the augmented subspace  $\mathcal{C}_s$  is equal

to  $[K_m \ U_r]$ .

**4.2. Test problems.** The matrices of tests arise from industrial applications in fluid dynamics and from convection-diffusion problems. The main characteristics are listed in Table 4.1

TABLE 4.1  
Characteristics of test matrices,  $N$ :Number of rows/columns,  $NNZ$ :Nonzero entries

Matrix	$N$	$NNZ$	geometry
IM07R	261,465	26,872,530	3D
VV11R	277,095	30,000,952	3D
RM07R	272,635	37,355,908	3D
3DCONSKY_121	1,771,561	50,178,241	3D
3DCONSKY_161	4,173,281	118,645,121	3D

The problems *IM07R*, *VV11R* and *RM07R* arise from design optimization in computational fluid dynamics simulations. They are provided by the FLUOREM company, a CFD software editor<sup>4</sup>. Table 4.1 lists the coefficient matrices with their main characteristics. The physical equations are the Reynolds-Averaged Navier-Stokes for compressible flows discretized using the finite volume methods as presented by [35]. The resulting matrix is formed of  $b \times b$  blocks where  $b$  is the number of fluid conservative variables (density, velocity, energy and turbulent variables). The matrix RM07R is available online in the University of Florida sparse matrix collection (see [14]) in the FLUOREM directory. The matrix is structurally symmetric in blocks. Regarding the values, the matrix is nonsymmetric and indefinite. In [33, 35], preliminary studies show that hybrid solvers based on GMRES and Schwarz-based preconditioners offer robust approaches to solve efficiently these systems. As pointed in [35], we avoid the ILU factorization in the subdomain matrices because of its unpredictable behavior. We therefore rely on a direct solver (MUMPS) within each subdomain.

The test cases *3DCONSKY\_121* and *3DCONSKY\_161* correspond to the *convective SkyScraper* problem in [1, 28]. The physical equation is given by the boundary value problem

$$\operatorname{div}(a(x)u) - \operatorname{div}(\kappa(x)\nabla u) = f \text{ in } \mu \quad (4.1)$$

$$u = 0 \text{ on } \partial\mu_D \quad (4.2)$$

$$\frac{\partial u}{\partial n} = 0 \text{ on } \partial\mu_N \quad (4.3)$$

where  $\mu = [0, 1]^3$ ,  $\partial\mu_N = \partial\mu \setminus \partial\mu_D$ . The tensor  $\kappa$  is isotropic and discontinuous. The domain contains many zones of high permeability which are isolated from each other. Let  $[x]$  denote the integer value of  $x$  then  $\kappa$  is given in 3D by

$$\kappa(x) = \begin{cases} 10^3 * ([10 * x_2] + 1), & \text{if } [10 * x_i] = 0 \text{ mod}(2), i = 1, 2, 3, \\ 1, & \text{otherwise} \end{cases} \quad (4.4)$$

The velocity field  $a = (1000, 1000, 1000)^T$  and  $f = x_1^2 + x_2^2 + x_3^2$ . The discretization is done using P2-type finite element methods in the Freefem++<sup>5</sup> package. We consider

<sup>4</sup>[www.fluorem.com/en/software/optimization/turb-opty-cfd](http://www.fluorem.com/en/software/optimization/turb-opty-cfd)

<sup>5</sup><http://www.freefem.org/ff++/index.htm>



a uniform grid with  $n \times n \times n$  nodes and we choose  $n = 121$  and  $161$ . During our numerical experiments, we rely on the  $ILLU(1)$  factorization to approximate the solutions on the subdomains induced by the additive Schwarz method.

**4.3. Platform of tests.** Experiments are done on a distributed memory super-computer *Vargas*<sup>6</sup> which has 3,584 Power6 CPUs. Each Power6 CPU is a dual-core 2-way SMT with a peak frequency at 4.7 GHz. The computer is made of 112 nodes connected through an Infiniband network. Each node has 32 Power6 CPUs that access 128GB of local memory in a non-uniform way (hardware NUMA nodes). The memory accessed by a single MPI process is limited to 3.2GB for the data and 0.5GB for the stack.

**4.4. Analysis of convergence with matrix *RM07R*.** We first consider the large test case *RM07R* from the FLUOREM collection and compare AGMRES( $m,r$ ) with GMRES( $m$ ). We first use AGMRES without deflation ( $r = 0$ ). The goal is to confirm that the two methods have the same convergence behavior for a reasonable restart length. After that, we show the benefits of using the deflation when the restart length in AGMRES is small and when the number of subdomains increases. We finish this section by giving the benefits of using an adaptive strategy.

In Figure 4.1, we plot the convergence of GMRES( $m$ ) and AGMRES( $m$ ) with three restart lengths,  $m = 32, 48$  and  $64$ . The number of subdomains is 32 and the LU factorization is used within the subdomains. The first remark from Figure 4.1 is that there is no real difference between the residual norm obtained from the two strategies. Secondly, the convergence curve of GMRES( $m$ ) indicates a periodic stagnation in the iterative process. These ticks occur at the time of restart and are more visible when  $m$  is small, hence the larger number of iterations. These ticks suggest that some information is lost at the time of restart and that the augmented basis could be beneficial to improve the convergence rate on these cases. The other test cases give similar behaviors.

Now we show the impact of deflation by augmenting the basis. In Figure 4.2, we give the convergence history of GMRES( $m$ ) and AGMRES( $m, r$ ) with  $m = 32, 48$  and  $r = 2$ , that is we compute two approximate eigenvectors at each restart and we use a basis of size  $s = m + 2$ . The number of subdomains is still 32. The adaptive strategy is not used at this point. It can be clearly noticed that adding only two eigenvectors in the basis is sufficient to speedup the convergence in AGMRES. For instance, GMRES(32) requires 886 iterations while AGMRES(32,2) needs almost 272 iterations. When we increase the restart length to 48, GMRES benefits greatly from that and requires almost 355 iterations to reach the desired accuracy while AGMRES(48,2) needs 250 iterations. The general notice here is that AGMRES(32,2) and AGMRES(48,2) have almost the same convergence rate while GMRES is more sensitive to the restart length. This is more visible when the number of subdomains vary.

The robustness of Schwarz preconditioners decreases as the number of subdomains increases. GMRES will thus require more and more iterations, particularly if the restart length is fixed. We show this behavior in Figure 4.3, where the restart length is fixed and the number of subdomains is increased. Clearly, as expected, the number of iterations in GMRES increases as we add more subdomains. For instance, GMRES(32) requires 886 iterations with 32 subdomains. With 64 subdomains, this number reaches 1000 iterations without reaching the prescribed tolerance of  $10^{-10}$ .

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<sup>6</sup><http://www.idris.fr/su/Scalaire/vargas/hw-vargas.html>

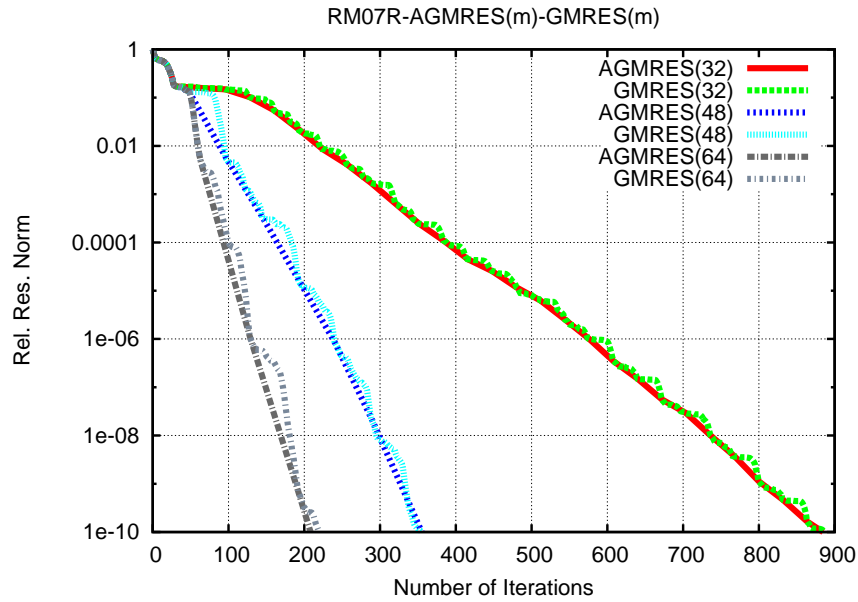


FIG. 4.1. *RM07R* : Influence of the restart length in *AGMRES* and *GMRES*, 32 subdomains

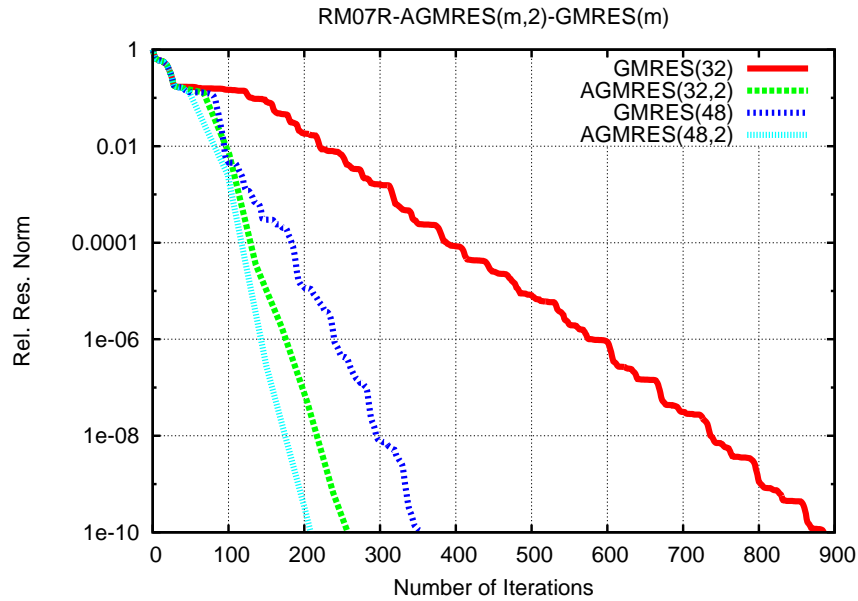


FIG. 4.2. *RM07R*: Influence of the augmented basis in *AGMRES* over *GMRES*, 32 subdomains

In  $\text{AGMRES}(m, r)$ , there is no such difference. As we increase the number of subdomains, we observe that the convergence rates remain quite close. Indeed,  $\text{AGMRES}(32, 2)$  requires respectively 272 and 311 iterations for 32 and 64 subdomains. The fact that the number of iterations increases only slightly when increasing  $D$  has

a great impact to the scalability of AGMRES. We give the timing results in the next section.

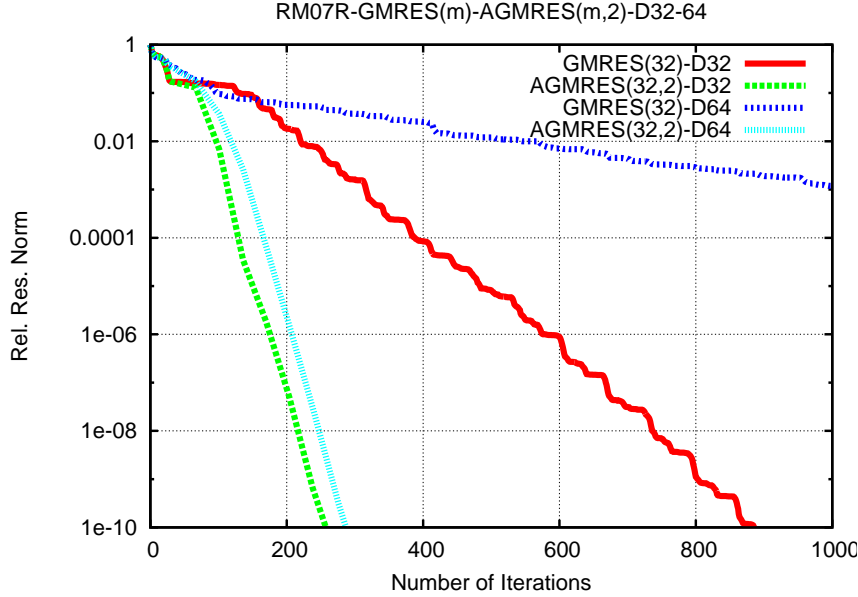


FIG. 4.3. *RM07R*: Influence of the number of subdomains in the convergence of GMRES. The restart length is fixed and the benefits of the augmented basis in AGMRES is given.

In GMRES, a better convergence rate can be obtained if the restart length is increased as a function of the number of subdomains. We show in Table 4.2 that in such case, it is still beneficial to have an augmented basis in AGMRES. These results

KSP $D \backslash m$	GMRES( $m$ )			AGMRES( $m, 2$ )			AGMRES( $m, 4$ )		
	32	48	64	32	48	64	32	48	64
8	93	70	57	100	98	57	105	100	57
16	254	169	123	169	148	130	177	153	132
32	886	355	220	272	250	196	212	205	200
64	-	702	445	311	303	265	287	258	270

TABLE 4.2

*RM07R*: Number of iterations in GMRES( $m$ ), AGMRES( $m, 2$ ) and AGMRES( $m, 4$ ) as a function of the number of subdomains in the restricted additive Schwarz

can be divided into three parts:

1. With 8 subdomains, GMRES needs less iterations than AGMRES for all values of the restart length. Note that this difference is mainly due to the fact that the stopping test is computed only at each outer cycle in AGMRES. The accuracy achieved in AGMRES for these cases is always better. Typically, AGMRES gives an accuracy of  $10^{-14}$  in the computed residual while it is  $10^{-11}$  in GMRES.

2. For the same reasons, AGMRES needs more iterations than GMRES for 16 subdomains and large value of  $m$ . However for small values of  $m$ , AGMRES is clearly better than GMRES.
3. From 32 subdomains, AGMRES needs less iterations than GMRES for all restart lengths. The dash in GMRES(32) for 64 subdomains denotes that the desired accuracy has not been reached within the 1,000 iterations allowed. On the contrary, it requires almost 300 iterations with AGMRES( $m, r$ ) to converge.

Thus, the main empirical conclusion from these experiments and others not reported here is that AGMRES is less sensitive to the restart length and the number of subdomains than GMRES. On the other hand, AGMRES is rather sensitive to the number of extracted eigenvectors. As for the basis size, it is difficult indeed to know how many vectors should be added to the basis to improve the convergence. If  $r$  is very large, the process of updating the eigenvectors could add more overhead. If  $r$  is small, the deflation could not be beneficial. The proposed adaptive strategy provides a trade-off between these two bounds.

If some information about the convergence behavior has been collected before, then it can be used to define the  $smv$  and  $bgv$  parameters in the adaptive strategy. Our goal is to show that this technique can be used to speedup the convergence by adaptively adjusting the frequency and the number of extracted eigenvalues. We take the smallest restart length  $m = 32$ , a large number of subdomains and the smallest number of harmonic Ritz vectors  $r = 1$ . Yet, we know from  $D = 16$  that GMRES(32) and thus AGMRES(32) needs roughly 254 iterations. From the adaptive strategy, we still set the maximum number of iterations  $itmax = 1,000$  but now we set  $smv = 0.1$  and  $bgv = 0.2$ . As explained in section 3.2.6,  $smv \times itmax$  defines the lower bound below which it is not beneficial to use an augmented basis, and  $bgv \times itmax$  defines the upper bound beyond which a slow convergence rate is expected and some action should be done. In this last case, we increase  $r$  by a fixed value  $l$ . We take  $l = 2$  in this case. Figure 4.4 gives the convergence history of AGMRES( $m, 1$ ) with  $m = 24$  and  $m = 32$ . It can be seen that when  $r = 1$  and without adaptive strategy, the augmented basis does not contain enough spectral information to speed up the convergence. When  $r$  is adaptively increased, the basis recovers more and more spectral information and the convergence rate gets better. At the coconvergence for instance,  $r = 3$  and  $r = 5$  respectively for AGMRES(24,1) and AGMRES(32,1) with the adaptive strategy while  $r = 1$  for the non adaptive strategy. It should be noted however that the actual limitation of the proposed adaptive strategy is the choice of the right values of  $smv$  and  $bgv$ . It is heuristic and problem-dependent. Nevertheless, if there are some experimental knowledge about the convergence of GMRES on similar problems, a good interval can be set with  $smv$  and  $bgv$  around  $itmax$  to detect a near-stagnation and switch to the augmented basis.

**4.5. Convergence analysis for the other matrices.** Now, we report the number of iterations in 4.3 for the two test cases *IM07R* and *VV11R*. AGMRES( $m, r$ ), we use  $r = 2$  and adaptively increase it until  $rmax = 5$ . As noted before, we see that for a fixed value of  $m$ , the number of iterations increases as  $D$  increases. It increases faster in GMRES than AGMRES. We note here again that deflation is needed to reach a good accuracy for a large  $D$ . With *IM07R* test case for instance and for 32 subdomains in the additive Schwarz, neither GMRES(24) nor GMRES(32) can produce the desired accuracy while AGMRES(32) requires 724 iterations to converge.

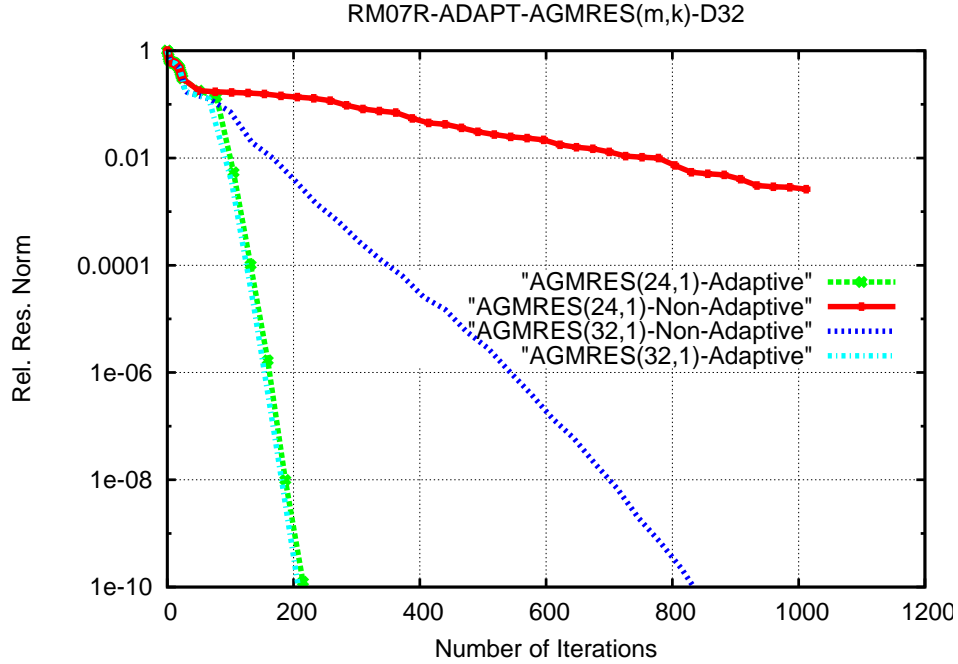


FIG. 4.4. *RM07R* : Benefits of the adaptive deflation strategy, Restart=24 and 32, 32 subdomains

KSP		GMRES( $m$ )			AGMRES( $m, 2$ )		
$m$		24	32	48	24	32	48
$D$							
	VV11R						
	8	251	191	147	248	172	146
	16	499	458	288	492	304	207
	32	-	957	670	641	541	516
IM07R							
8	240	235	189	249	203	195	
16	695	623	521	378	370	316	
24	927	913	759	492	444	408	
32	-	-	833	724	629	579	

TABLE 4.3

*VV11R* & *IM07R*: Number of iterations in GMRES( $m$ ), AGMRES( $m, r$ ) as a function of the number of subdomains in the restricted additive Schwarz,  $r$  is adaptively increased until  $r_{max} = 5$ .

We end this section by considering the two matrices arising from the convection-diffusion problem. In Table 4.4, we give the number of matrix-vectors. Unlike the previous test cases, GMRES here is less sensitive to the restart parameter and the variation of subdomains. Hence the augmented basis is not as beneficial to the convergence as in the previous cases. Nevertheless, AGMRES is still faster than GMRES if we consider the parallel efficiency. This is the aim of the next sections.

Matrix	3DCONSKY_121		3DCONSKY_161	
$D \backslash m$	GMRES(16)	AGMRES(16,1)	GMRES(16)	AGMRES(16,1)
16	158	169	229	177
32	164	141	251	177
64	170	141	261	177
128	180	141	262	177
256	202	159	266	195

TABLE 4.4

Number of matrix-vector products in GMRES and AGMRES for the test problems 3DCONSKY\_121 and 3DCONSKY\_161

**4.6. Analysis of the CPU time.** To better show the benefits of using an augmented subspace approach with the Newton basis, we analyze in this section the timing results. The paramount goal when showing these results is that, as we increase the number of subdomains, we should be able to get a decrease during the iterative time. In GMRES( $m$ ) and AGMRES( $m$ ), the best way is undoubtedly to increase the restart length as well. Even then, the time will not decrease efficiently because of the negative effects of the restarting procedure and the weakness of one-level Schwarz preconditioner. In AGMRES( $m, r$ ), only a few extracted Ritz vectors are sufficient to decrease the time and obtain a significant efficiency.

In Table 4.5, We compare GMRES( $m$ ), AGMRES( $m$ ) and AGMRES( $m, r$ ) on the test case *RM07R* by varying the number of subdomains  $D$ , the restart length  $m$  and the number of harmonic Ritz values  $r$  which increases adaptively until  $r_{max} = 5$ . The number of MPI processes is equal to the number of subdomains. The total time is the CPU time required to perform all the steps in Algorithm 2. The iterative time is the time spent in the step 7. The setup time is the difference between the two times. It is independent of the method and of  $m$ . It decreases when  $D$  increases because the subdomains become smaller and the  $LU$  factorizations are faster. Thus, we concentrate from now on the iterative time. The time per iteration is the time of one cycle divided by the number of matrix-vectors products in the cycle, which is  $m$  or  $m + r$ . It includes the time to compute the orthonormal basis (with Arnoldi GMRES or the  $QR$  factorization for AGMRES) and the time to update the eigenvectors  $U$  for AGMRES( $m, r$ ). The iterative time is thus the product of the time per iteration by the number of iterations. The behaviors of both GMRES( $m$ ) and AGMRES( $m$ ) are similar. Increasing  $m$  has two opposite effects: it decreases the number of iterations (in some cases, the number of cycles remain the same for AGMRES) and increases the time per iteration, because of the orthogonalization steps. Thus, in most cases, there is an optimal value of  $m$ , which depends on  $D$ , with a minimal iterative time. Increasing  $D$  has also two opposite effects, but in the reverse way: it increases the number of iterations and decreases the time per iteration, thus there is in general an optimal value of  $D$ , which depends on  $m$ . Even though their behavior are similar, AGMRES( $m$ ) clearly performs faster than GMRES( $m$ ), for all but one configurations. This is mainly due to a faster time per iteration thanks to a more efficient parallel algorithm. This is explored in the next section by analyzing the communication volume.

The objective of deflation in AGMRES( $m, r$ ) is two-fold: to get an algorithm less sensitive to  $m$  and to increase the number of subdomains (thus the number of MPI

$D$	Algo.	Total Time	Iter. Time	Time/Iter	MSG ( $\times 10^4$ )
8	GMRES(32)	427.3	327.33	3.52	1.74
	GMRES(48)	386.1	291.64	4.166	1.41
	GMRES(64)	358.1	264.58	4.64	1.03
	AGMRES(32)	358.5	263.08	2.74	1.3
	AGMRES(48)	369.1	271.9	2.832	1.45
	AGMRES(64)	329.4	236.76	4.228	1.23
	AGMRES(32,2)	347.4	257.11	2.624	1.32
	AGMRES(48,2)	373.1	277.98	2.837	1.48
AGMRES(64,2)	329.4	236.76	4.228	1.23	
16	GMRES(32)	379.3	349.97	1.378	13.1
	GMRES(48)	333.1	302.66	1.791	9.05
	GMRES(64)	286.8	257.03	2.09	6.88
	AGMRES(32)	305.8	276.1	1.079	8.1
	AGMRES(48)	263.0	230.5	1.201	6.78
	AGMRES(64)	256.8	227.82	1.78	5.56
	AGMRES(32,2)	224.1	193.39	1.316	9.84
	AGMRES(48,2)	240.9	210.56	1.376	10.01
AGMRES(64,2)	231.4	201.05	1.547	5.66	
32	GMRES(32)	573.4	557.13	0.629	96.25
	GMRES(48)	239.5	223.54	0.63	39.74
	GMRES(64)	158.4	139.2	0.633	25.38
	AGMRES(32)	273.0	256.91	0.287	54.97
	AGMRES(48)	167.1	150.84	0.393	25.93
	AGMRES(64)	131.4	114.83	0.449	19.42
	AGMRES(32,4)	91.41	75.23	0.357	31.83
	AGMRES(48,4)	94.79	79.028	0.38	33.9
AGMRES(64,4)	99.45	83.148	0.406	32.24	
64	GMRES(32)	-	-	-	-
	GMRES(48)	214.8	204.16	0.291	227.02
	GMRES(64)	165.6	156.44	0.352	145.69
	AGMRES(32)	-	-	-	-
	AGMRES(48)	167.0	157.72	0.219	132.42
	AGMRES(64)	97.87	86.066	0.192	88.67
	AGMRES(32,4)	62.39	52.839	0.202	101.53
	AGMRES(48,4)	67.0	57.733	0.22	110.99
AGMRES(64,4)	63.15	53.788	0.203	116.08	

TABLE 4.5

Timing statistics for RM07R;  $D$ : Number of subdomains and number of MPI processes. Total Time: CPU elapsed time in seconds, Iter. Time: CPU time in the iterative phase. Time/Iter : average time spent in each iteration (matrix-vector product and preconditioning step). MSG: MPI messages and reductions. With AGMRES( $m, r$ ),  $r$  is adaptively increased until  $rmax = 5$ .

processes). For  $D$  fixed, there is still an optimal value of  $m$  but it is smaller. The iterative time decreases from  $D = 8$  until  $D = 64$ . Thus our method allows to choose a small value of  $m$  and to reduce the CPU time with a large number of subdomains. We get indeed a more efficient parallelism because the number of iterations does not inflate. Clearly, AGMRES( $m, r$ ) gives the smallest CPU time. These results are confirmed with other test cases as shown in Table 4.6 and Figures 4.5 and 4.6.

It is better for GMRES( $m$ ) to choose a small number of subdomains  $D$  and a large restart  $m$ . On the contrary, it is more efficient to choose a large number of

$D \backslash m$	24		32		48		
	Iter. Time	MSG	Iter. Time	MSG	Iter. Time	MSG	
GMRES( $m$ )							
8	92.84	2.05	68.95	1.69	77.7	1.47	VV11R
16	101.1	12.27	89.37	11.47	63.2	7.66	
32	-	-	31.2	22.5	29.7	18.54	
AGMRES( $m, 2$ )							
8	52.8	1.28	38.5	1.02	40.5	1.05	VV11R
16	51.8	7.4	34.5	4.91	28.08	3.87	
32	38.3	25.6	31.2	22.5	29.7	18.5	
GMRES( $m$ )							
8	76.219	2.6	73.3	2.63	63.669	2.31	IM07R
16	111.74	20.06	96.246	18.25	83.583	15.76	
32	-	-	-	-	77.066	59.87	
AGMRES( $m, 2$ )							
8	45.781	1.65	40.905	5.48	40.85	1.52	IM07R
16	36.492	21.65	34.803	24.12	33.65	23.64	
32	33.262	94.54	27.837	93.27	27.109	105.35	

TABLE 4.6

Timing statistics in GMRES and AGMRES for test cases VV11R and IM07R.  $D$ : Number of subdomains and number of MPI processes. Iter. Time : time spent in the iterative phase. MSG: MPI messages and reductions. With AGMRES( $m, r$ ),  $r$  is adaptively increased until  $r_{max} = 5$ .

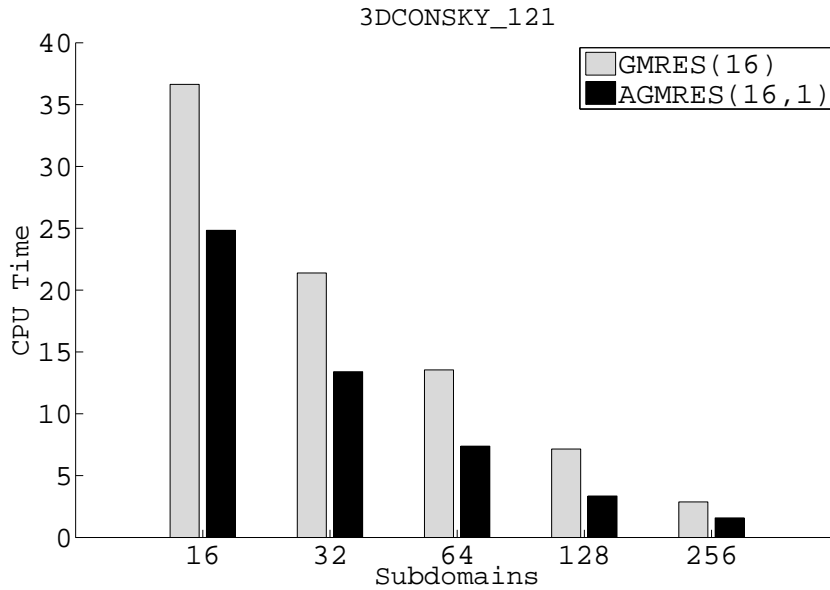


FIG. 4.5. CPU Time in the iterative phase for the 3D  $121 \times 121 \times 121$  convective SkyScraper problem (Matrix size 1,771,561; Nonzeros 50,178,241); 16 to 256 subdomains, ILU(1) in subdomains;  $m = 16$ ;  $r = 1$



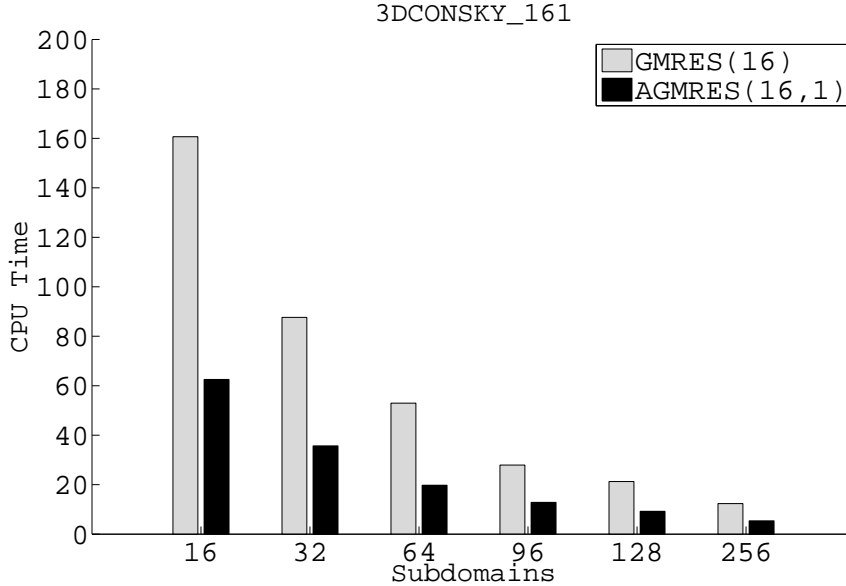


FIG. 4.6. CPU Time in the iterative phase of GMRES and AGMRES for the 3D  $161 \times 161$  convective SkyScraper problem ( Matrix size  $4,173,281$ ; Nonzeros  $118,645,121$ ); 16 to 256 subdomains,  $ILU(1)$  in subdomains;  $m = 16$ ;  $r = 1$

subdomains  $D$  and a small restart  $m$  with our method  $AGMRES(m, r)$ . Clearly,  $AGMRES(m, r)$  is faster than  $GMRES(m)$ . In order to compare the methods with similar memory requirements, we choose  $m = 24$  for AGMRES and  $m = 48$  for GMRES, since AGMRES needs to store the two systems  $W_s$  and  $V_s$ . For all but one values of  $D$ ,  $AGMRES(24, r)$  is faster than  $GMRES(48)$ , for both matrices VV11R and IM07R. It is also true for  $AGMRES(32, r)$  compared with  $GMRES(64)$  for the matrix RM07R.

**4.7. Analysis of parallelism.** The other advantage of AGMRES over GMRES is the communication volume. In Tables 4.5 and 4.6 and in Figure 4.7, we have reported the number of MPI messages exchanged. The counts are done on the Send/Receive routines as well as the collective communications (Reduce and Broadcast). We do not take into account the MPI message lengths. It appears first that the number of messages is a function of the number of subdomains. This is generally reduced by allowing many subdomains to be assigned to a unique CPU. In the problems under study, this is not feasible in practise as it will induce more iterations as the subdomains increase. The communication volume is obviously proportional to the number of iterations as well. The second observation is that AGMRES communicates less than GMRES for the same number of subdomains and the same basis size. As more subdomains are used, the gap between the two methods increase. For instance, in Table 4.5, GMRES on 64 subdomains produces nearly a ratio of 1.5 more messages than AGMRES. In the augmented basis, the situation is different. At each cycle,  $AGMRES(m, r)$  communicates more than  $AGMRES(m)$  because of the computation of the eigenvectors. However, since a substantial number of iterations is saved by using the augmented basis, we observe actually a better communication in  $AGMRES(m, r)$ .

Now between GMRES and  $\text{AGMRES}(m, r)$ , the previous analysis holds as well but there are two situations: when the restart length is very close to the number of subdomains, then the communication for the computation of eigenvectors may dominate if there is no substantial acceleration in the convergence rate of  $\text{AGMRES}(m, r)$ . This is observed in Table 4.6 for *VV11R* and *IM07R*. With a substantial gain in the convergence rate as in Table 4.5,  $\text{AGMRES}(m, r)$  benefits from that and the communication volume decreases proportionally to the number of iterations. The second situation is when the number of subdomains is very large with respect to the basis size. Even if there is no substantial acceleration in  $\text{AGMRES}(m, r)$ , the kernel computations of  $\text{AGMRES}$  will produce less communication volume than that in GMRES. This is observed in Figure 4.7. As the number of subdomains increase, the difference between the two methods are more and more distincts. Between the two situations, a fine-tuned adaptive strategy is still required to determine whether or not to augment the basis.

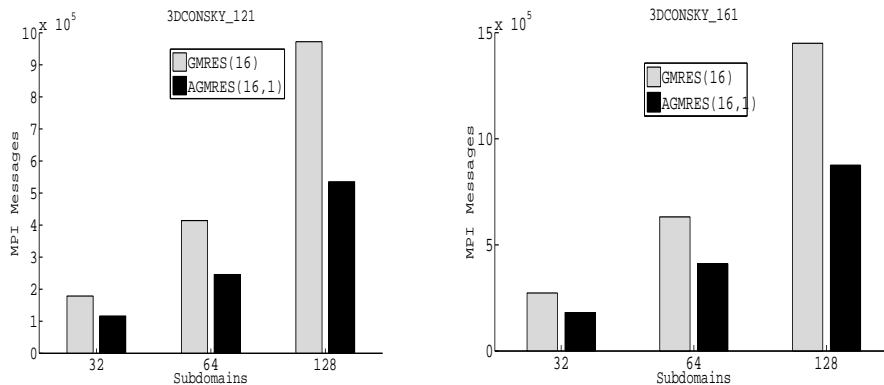


FIG. 4.7. Amount of MPI Messages in the iterative phase of GMRES and AGMRES for the convective skyscraper problems on the 3D  $121 \times 121 \times 121$  and  $161 \times 161 \times 161$  grids

**5. Concluding remarks.** We have proposed the  $\text{AGMRES}(m, r)$  implementation, which combines the Newton basis GMRES implementation with the augmented subspace technique. This approach benefits from the high level of parallelism during the kernel computation of the Krylov basis. The proposed augmented basis reduces the negative effects due to restarting and to a large number of subdomains.

The numerical results on the VARGAS supercomputer (IBM Power 6 processors) confirm that  $\text{AGMRES}$  communicates less than GMRES and produces a faster solution of large linear systems. Moreover, on the proposed test cases,  $\text{AGMRES}$  gives a fairly good convergence rate when few eigenvectors are added to the Krylov basis. The proposed implementation is done in the PETSc package. It thus benefits from the optimized routines for the usual linear algebra operations on matrices and vectors. Its object-oriented interface allows to use transparently any parallel preconditioner implemented in the package, based on algebraic domain decomposition methods or multilevel methods. It can be used indeed as a smoother for algebraic multigrid methods [18].

Although the proposed augmented basis behaves well on the proposed test cases, there are some cases where it may not be useful and thus expensive to use. Hence a good analysis is still needed in the adaptive strategy to avoid the computation of

eigenvectors on such cases.

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#### REFERENCES

- [1] Y. ACHDOU AND F. NATAF, *Low frequency tangential filtering decomposition*, Numerical Linear Algebra with Applications, 14 (2007), pp. 129–147.
- [2] P. R. AMESTOY, I. S. DUFF, J.-Y. L'EXCELLENT, AND J. KOSTER, *A fully asynchronous multifrontal solver using distributed dynamic scheduling*, SIAM Journal on Matrix Analysis and Applications, 23 (2001), pp. 15–41.
- [3] P. R. AMESTOY, I. S. DUFF, D. RUIZ, AND B. UÇAR, *A parallel matrix scaling algorithm*, in High Performance Computing for Computational Science - VECPAR 2008, J. M. Palma, P. R. Amestoy, M. Daydé, M. Mattoso, and J. a. C. Lopes, eds., Berlin, Heidelberg, 2008, Springer-Verlag, pp. 301–313.
- [4] G.-A. ATENEKENG-KAHOU, *Parallélisation de GMRES préconditionné par une itération de Schwarz multiplicatif*, PhD thesis, University of Rennes 1 and University of Yaounde 1, 2008. <ftp://ftp.irisa.fr/techreports/theses/2008/atenekeng.pdf>.
- [5] J. BAGLAMA, D. CALVETTI, G. H. GOLUB, AND L. REICHEL, *Adaptively preconditioned GMRES algorithms*, SIAM J. Sci. Comput., 20 (1998), pp. 243–269.
- [6] Z. BAI, D. HU, AND L. REICHEL, *A Newton basis GMRES implementation*, IMA J Numer Anal, 14 (1994), pp. 563–581.
- [7] S. BALAY, J. BROWN, , K. BUSCHELMAN, V. EIJKHOUT, W. D. GROPP, D. KAUSHIK, M. G. KNEPLEY, L. C. MCINNES, B. F. SMITH, AND H. ZHANG, *PETSc users manual*, Tech. Report ANL-95/11 - Revision 3.2.0, Argonne National Laboratory, 2011.
- [8] S. BALAY, K. BUSCHELMAN, W. D. GROPP, D. KAUSHIK, M. G. KNEPLEY, L. C. MCINNES, B. F. SMITH, AND H. ZHANG, *PETSc Web page*, 2011. <http://www.mcs.anl.gov/petsc>.
- [9] M. BENZI, *Preconditioning techniques for large linear systems: a survey*, J. Comput. Phys., 182 (2002), pp. 418–477.
- [10] K. BURRAGE AND J. ERHEL, *On the performance of various adaptive preconditioned GMRES strategies*, Numerical Linear Algebra with Applications, 5 (1998), pp. 101–121.
- [11] X.-C. CAI AND M. SARKIS, *A restricted additive Schwarz preconditioner for general sparse linear systems*, SIAM J. Sci. Comput., 21 (1999), pp. 792–797 (electronic).
- [12] A. CHAPMAN AND Y. SAAD, *Deflated and augmented Krylov subspace techniques*, Numerical Linear Algebra with Applications, 4 (1997), pp. 43–66.
- [13] R. DA CUNHA, D. BECKER, AND J. PATTERSON, *New parallel (rank-revealing) QR factorization algorithms*, in Euro-Par 2002 Parallel Processing, B. Monien and R. Feldmann, eds., vol. 2400 of Lecture Notes in Computer Science, Springer Berlin / Heidelberg, 2002, pp. 209–237.
- [14] T. A. DAVIS AND Y. HU, *The University of Florida Sparse Matrix Collection*, ACM Transactions on Mathematical Software, 38 (2011).
- [15] E. DE STURLER, *Iterative Methods on Distributed Memory Computers*, PhD thesis, Delft University of Technology, Delft, The Netherlands, October 1994.
- [16] J. DEMMEL, L. GRIGORI, M. F. HOEMMEN, AND J. LANGOU, *Communication-optimal parallel and sequential QR and LU factorizations*, SIAM journal on Scientific Computing (to appear), (2011).
- [17] M. EIERMANN, O. G. ERNST, AND O. SCHNEIDER, *Analysis of acceleration strategies for restarted minimal residual methods*, J. Comput. Appl. Math., 123 (2000), pp. 261–292. Numerical analysis 2000, Vol. III. Linear algebra.

- [18] H. C. ELMAN, O. G. ERNST, AND D. P. O'LEARY, *A multigrid method enhanced by Krylov subspace iteration for discrete Helmholtz equations*, SIAM J. Sci. Comput., 23 (2001), pp. 1291–1315 (electronic).
- [19] J. ERHEL, *A parallel GMRES version for general sparse matrices*, Electronic Transaction on Numerical Analysis, 3 (1995), pp. 160–176.
- [20] ———, *A parallel preconditioned GMRES algorithm for sparse matrices*, in The mathematics of numerical analysis, vol. 32 of Lectures in Appl. Math., AMS, Providence, RI, 1996, pp. 345–355.
- [21] J. ERHEL, *Some properties of Krylov projection methods for large linear systems*, vol. 3 of Computational Technology Reviews, Saxe-Coburg Publications, 2011, pp. 41–70.
- [22] J. ERHEL, K. BURRAGE, AND B. POHL, *Restarted GMRES preconditioned by deflation*, Journal of Computational and Applied Mathematics, 69 (1996), pp. 303–318.
- [23] M. HOEMMEN, *Communication-avoiding Krylov subspace methods*, PhD thesis UCB/EECS-2010-37, UC Berkeley, 2010.
- [24] W. JALBY AND B. PHILIPPE, *Stability analysis and improvement of the block Gram-Schmidt algorithm*, SIAM J. Sci. Statist. Comput., 12 (1991), pp. 1058–1073.
- [25] W. JOUBERT AND G. CAREY, *Parallelizable restarted iterative methods for nonsymmetric linear systems. part II: Parallel implementation*, Intern. J. Computer Math., 44 (1992), pp. 269–290.
- [26] S. A. KHARCHENKO AND A. Y. YEREMIN, *Eigenvalue translation based preconditioners for the GMRES(k) method*, Numer. Linear Algebra Appl., 2 (1995), pp. 51–77.
- [27] S. KIM AND A. CHRONOPOULOS, *An efficient parallel algorithm for extreme eigenvalues of sparse nonsymmetric matrices*, International Journal of High Performance Computing Applications, 6 (1992), pp. 407–420.
- [28] P. KUMAR, L. GRIGORI, F. NATAF, AND Q. NIU, *Combinative preconditioning based on Relaxed Nested Factorization and Tangential Filtering preconditioner*, Research Report RR-6955, INRIA, 2009.
- [29] M. MOHIYUDDIN, M. HOEMMEN, J. DEMMEL, AND K. YELICK, *Minimizing communication in sparse matrix solvers*, in SC '09: Proceedings of the Conference on High Performance Computing Networking, Storage and Analysis, New York, NY, USA, 2009, ACM, pp. 1–12.
- [30] R. B. MORGAN, *A restarted GMRES method augmented with eigenvectors*, SIAM J. Matrix Anal. Appl., 16 (1995), pp. 1154–1171.
- [31] ———, *GMRES with deflated restarting*, SIAM J. Sci. Comput., 24 (2002), pp. 20–37 (electronic).
- [32] D. NUENTSA WAKAM AND G.-A. ATENEKENG KAHOU, *Parallel GMRES with a multiplicative Schwarz preconditioner*, ARIMA Rev. Afr. Rech. Inform. Math. Appl. (to appear), (2010). Also Research report INRIA RR-7342.
- [33] D. NUENTSA WAKAM, J. ERHEL, E. CANOT, AND G.-A. ATENEKENG KAHOU, *A comparative study of some distributed linear solvers on systems arising from fluid dynamics simulations*, in Parallel Computing: From Multicores and GPU's to Petascale, vol. 19 of Advances in Parallel Computing, IOS Press, 2010, pp. 51–58.
- [34] D. NUENTSA WAKAM, J. ERHEL, AND W. D. GROPP, *Parallel adaptive deflated GMRES*, in Proceedings of DD'20, UC San Diego, in revision, 2011.
- [35] F. PACULL, S. AUBERT, AND M. BUISSON, *Study of ILU factorization for schwarz preconditioners with application to computational fluid dynamics*, in Proceedings of the Second International Conference on Parallel, Distributed, Grid and Cloud Computing for Engineering, Civil-Comp Press, Stirlingshire, UK, 2011.
- [36] B. PHILIPPE AND L. REICHEL, *On the generation of Krylov subspace bases*, Applied Numerical Mathematics, In Press (2011).
- [37] L. REICHEL, *Newton interpolation at Leja points*, BIT Numerical Mathematics, 30 (1990), pp. 332–346. 10.1007/BF02017352.
- [38] Y. SAAD, *Iterative methods for sparse linear systems*, Society for Industrial and Applied Mathematics, Philadelphia, PA, second ed., 2003.
- [39] Y. SAAD AND M. H. SCHULTZ, *GMRES: A generalized minimal residual algorithm for solving nonsymmetric linear systems*, SIAM Journal on Scientific and Statistical Computing, 7 (1986), pp. 856–869.
- [40] R. B. SIDJE, *Alternatives for parallel Krylov subspace basis computation*, Numerical Linear Algebra with Applications, 4 (1997), pp. 305–331.

- [41] R. B. SIDJE AND B. PHILIPPE, *parallel krylov subspace basis computation*, in CARI'94, 2ème colloque africain sur la recherche en Informatique, 1994.
- [42] V. SIMONCINI, *On a non-stagnation condition for GMRES and application to saddle point matrices*, Electron. Trans. Numer. Anal., 37 (2010), pp. 202–213.
- [43] V. SIMONCINI AND D. B. SZYLD, *Recent computational developments in Krylov subspace methods for linear systems*, Numer. Linear Algebra Appl., 14 (2007), pp. 1–59.
- [44] ———, *New conditions for non-stagnation of minimal residual methods*, Numer. Math., 109 (2008), pp. 477–487.
- [45] M. SOSONKINA, L. T. WATSON, R. K. KAPANIA, AND H. F. WALKER, *A new adaptive GMRES algorithm for achieving high accuracy*, Numer. Linear Algebra Appl., 5 (1998), pp. 275–297.
- [46] H. A. VAN DER VORST AND C. VUIK, *The superlinear convergence behaviour of GMRES*, J. Comput. Appl. Math., 48 (1993), pp. 327–341.